Maintaining production while reducing local and global environmental emissions in dairy farming

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Abstract: While milk is a major agricultural commodity, dairy farming also supports a large share of global beef production. In Life Cycle Assessment (LCA) studies of dairy farming systems, dairy-beef production is often ignored or 'allocated off', which may give a distorted view of production efficiencies. This study combines LCA with Data Envelopment Analysis (DEA) to develop an indicator of eco-efficiency for each of 738 UK dairy farms (3624 data points in 15 years) that aggregates multiple burdens and expresses them per unit of milk and dairy-beef produced. Within the DEA framework, the importance (weight) of dairy-beef relative to milk is iteratively increased to quantify the environmental losses from heavily focussing on milk-production, via e.g. higher yields per cow, with consequent lower burdens per unit of milk, yet with lower dairy-beef production levels, where burdens for beef production are externalized. Then, the relationship between DEA eco-efficiency and a series of indicators of dairy farming intensity at animal- and farm-levels was studied with Generalized Additive Models (GAM). For all sets of DEA weights (proportion of deviance explained ranged between 68% and 82%) indicate that milk yield per cow and forage area, and larger dairy herds all have a positive effect on eco-efficiency, while concentrate fed per unit of milk and the forage area both have a negative effect ($p < 0.05$ for all modelled relationships). These findings suggest that more intensive and consolidated dairy farms can positively impact on eco-efficiency. However, as the DEA weight for dairy-beef relative to milk increases, the relationship between environmental efficiency and farming specialization (expressed as L milk per kg dairy-beef produced) reverses from positive to negative. In conclusion, dairy-beef production is pivotal in determining the wider environmental efficiency of dairy (and ruminant food) systems, and its under-representation in efficiency studies has generated a misleading approach to meeting emission targets.

Title page

Maintaining production while reducing local and global environmental emissions in dairy farming

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***Cover Letter**

Dear Dr de Lange,

Thank you very much for handling our manuscript. We have made significant improvements in the abstract, introduction, methods and discussion in order to satisfactorily address all comments by the reviewers.

Please find attached our responses to the reviewers' comments.

Thank you.

Best regards,
Andreas Soteriades and co-authors

***Response to Reviewers**

Reviewer #2: I think that the manuscript may be published in this way. Indeed, the article is considered to be very effective and rich in terms of both scientific and theoretical and applicability.

Much appreciated, thank you.

Reviewer #3: Using traditional DEA method and taking the dairy farms as DMUs, this paper discusses the DEA eco-efficiency of each farm's outputs and burden, trade-offs between milk and dairy-beef production, and trade-offs between environmental burdens in England and Wales. The findings of this paper are interesting and have a scientific significance to understand trade-offs between agricutural production and environmental sustainbility.

Specific:

1. The title of the article refers to "sustainable dairy farming", but there is no clear research content in the text to answer the title. How does the author define sustainable farming?

It is a good point that 'sustainable farming' is a term with a variety of definitions, encompassing at least the environmental dimension, but normally economic and social dimensions as well. It may be challenging to strictly restrict the term to a single and comprehensive definition, and we have unintentionally abused its use in the title of our manuscript. We have changed the title.

2. The abstract of this paper does not clearly show the purpose, scientific significance, specific data, research methods and clear results of this study, which needs further modification and improvement.

We have revised the abstract to address the reviewer's requirements.

3. Unqualified Introduction. There is not enough literature reviewing and not clear research progress. It is necessary to further systematically, comprehensively and clearly summarize the current situation, hot topics, difficulties, problems and trends of existing research in this field, and clearly put forward the necessity, purpose, significance and main scientific issues of this research.

This is a fair point by the reviewer and we have revised the introduction to make clearer the links between diary emissions and national inventory policies and the value of the dairy sector as a case study for maintain or increasing production while not displacing emissions between countries and sectors. As part of this edit we have also added some additional literature including more recent papers.

4. Although Model 1 is a simple weighted summation formula, the author's existing description will still be confusive. What exactly does DMU0 refer to? It refers to any of the *n* DMUs for which the DEA model is run. This is standard DEA notation for explaining how the model works for a single DMU, without loss of generality. This is now explained in-text, just before the presentation of Model 1. What is the relationship between DMU0 and maxw, v? We are unsure what the question is about? We presume it also relates to the earlier question about notation? We have changed the notation to make explicit the fact that, for each farm, the weights *w* and *v* are farm-specific, i.e. w_o and v_o. So, for the optimal weights w^*_{ro} and v^*_{io}, we get the optimal efficiency score θ^*_o for DMU_o. Should it not be DMUj? See earlier answers. Although the author has listed several references, they should also be made clear. We are not entirely sure what is being asked for here? We have cited a number of DEA references that we deem as most important and relevant to this study, and have explained in what sense they are important and relevant. For example, we have cited the classic- and one of the most fundamental- DEA textbook of Cooper et al (2007). Similarly, we make mention of the studies of Jan et al 2012, Picazo-Tadeo et al 2011 and Soteriades et al 2016 because they present novel DEA applications in sustainable/eco-efficient dairy/agriculture using a variety of novel DEA-based methods and approaches. Finally, the studies of Camanho and Dyson (2005) and Soteriades et al (2018b) attempt to make DEA accessible to the lay practitioner by very simply explaining the more complex concepts characterizing DEA, using visual means and oversimplified examples.

5. What are the principles, basis and theoretical framework of user-defined burden weights and outputs weights?

Please see the three first new paragraphs in 2.2.3. (previously 2.1.3.) for a detailed answer to your question.

6. It is recommended to put Section 2.4 at the 2.1, otherwise some of the results of the previous study will appear to have no data source.

Done

7. How is the five aforemented burdens calculated? What is the relationship between this study and the previous studies of Soteriades et al (2019)?

We have revised section 2.1 (what used to be 2.4) to include more detail about the LCA process. The current study uses the same farm dataset used in Soteriades et al (2019), who also calculated the farm-specific burdens used here. The process for calculating the burdens is an adaptation of the modelling of Soteriades et al (2018) who, in turn, used equations and emissions factors from Styles et al (2015, 2018). We appreciate that this may not have been entirely clear in the earlier version of our manuscript. We hope that the new section 2.1 satisfactorily addresses your questions.

8. Section 3.4 seems strange. At first glance, "Methodology" is easy to cause ambiguity here? Nevertheless, the content of "Methodology" discussion here should also make a comparative analysis between the results of this paper and the existing relevant research results, and the results of other scholar's, in order to verify the effectiveness and reliability of this research?

We have now completely revised section 3.4.

- An aggregate indicator dairy farm environmental efficiency was calculated
- The indicator accounted for dairy-beef production in addition to milk output
- The relative weight of dairy-beef-to-milk was simulated at varying levels
- The relationship between farming intensity and environmental efficiency was modeled
- Dairy-beef played a key role in determining dairy farm environmental efficiency

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Abstract

While milk is a major agricultural commodity, dairy farming also supports a large ~~significant amount~~ share of global beef production. In Life Cycle Assessment (LCA) studies of dairy farming systems, dairy-beef production is often ignored or 'allocated off', which may give a distorted view of production efficiencies. This study combines LCA with Data Envelopment Analysis (DEA) to develop an indicator of eco-efficiency for each of 738 UK dairy farms (3624 data points in 15 years) that aggregates multiple burdens and expresses them per unit of milk *and* dairy-beef produced. ~~As milk production efficiencies have been improving over time, the same or more milk is produced by fewer dairy cows. Consequently, less dairy-beef is available in total and per unit of milk produced.~~ Both ~~Moreover, dairy~~ and beef ~~farming~~ are~~is responsible for multiple environmental impacts on the atmosphere, land and water. Studies on the relationships between environmental efficiency (that is, burdens per unit of product) and dairy farming intensity tend to focus solely on the milk produced. This may give a distorted view of production efficiencies, because dairy-beef production is either ignored or 'allocated off'. This study explores the relationships between environmental efficiency (Life Cycle Assessment-derived burdens) and farming intensity through a mathematical~~Within the DEA framework, ~~that iteratively increases~~ the importance (weight) of dairy-beef relative to milk is iteratively increased to quantify the environmental losses from heavily focussing on milk-production, via e.g. higher yields per cow, with consequent lower burdens per unit of milk, yet with lower dairy-beef production levels, where burdens for beef production are externalized. Then, the relationship between DEA eco-efficiency and a series of indicators of dairy farming intensity at animal- and

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farm-levels was studied with Generalized Additive Models (GAM). For all sets of DEA weights (proportion of deviance explained ranged between 68% and 82%) indicate that milk yield per cow and forage area, and larger dairy herds all have a positive effect on eco-efficiency, while concentrate fed per unit of milk and the forage area both have a negative effect ($p < 0.05$ for all modelled relationships). These findings suggest that more intensive and consolidated dairy farms can positively impact on eco-efficiency. However~~The main finding is that~~, as~~while~~ the DEA weight for dairy-beef relative to milk increases, the relationship between environmental efficiency and farming specialization (expressed as L milk per kg dairy-beef produced) reverses from positive to negative. In conclusion, dairy-beef production is pivotal in determining the wider environmental efficiency of dairy (and ruminant food) systems, and its under-representation in ~~from e~~efficiency studies ~~hs~~has generated ~~give~~ a misleading approach to meeting emission targets~~picture~~.

Life Cycle Assessment; Dairy-beef production; Production intensity; Commercial farm panel data; Data Envelopment Analysis; Generalized Additive Models.

Word count: 6202 words.

1. Introduction

Milk is one of the most produced and valuable agricultural commodities worldwide, contributing 27% and 10% to the global value added of livestock and agriculture respectively (FAO 2018a). Nevertheless, dairy production is also responsible for a large share of environmental burdens, including greenhouse gas emissions, nutrient losses to air and water, water consumption and land use (FAO 2016, 2018b, Steinfeld *et al* 2006). Reductions in greenhouse gas emissions are increasingly driven by national emission targets, for example the UK has a legally binding net-zero target by 2050. Efforts to reduce the environmental impacts of dairy farming have largely focussed on improving milk production intensity, particularly producing more milk from fewer cows~~-~~ (Gerber *et al* 2011, 2013, Gonzalez-Mejia *et al* 2018, Zehetmeier *et al* 2012). Assessed in isolation this approach has been very successful in reducing emissions per unit of production, for example in the USA emissions per unit of milk in 2017 were 80.8% of those in 2007 (Capper and Cady 2019). However, reductions in national emissions can be undesirably achieved by displacing emissions overseas and reductions in sectoral emissions can be displaced to other sectors. The dairy industry is a good case study of both these potential undesirable outcomes. In intensive dairy production, imported feed represents a large overseas footprint even in countries such as Sweden where environmental policy aims to reduce emissions without increasing impacts overseas (Cederberg *et al* 2019). ~~This, however,~~At the sectoral level, ~~-~~reducing~~es~~ the size of the dairy herd ~~and consequently ignores that dairy farming also makes a significant~~reduces potential beef supply currently 45% ~~%~~ ~~contribution to the~~of global beef supply (Opio *et al* 2013, Vellinga and de Vries 2018)~~ from surplus calves and culled cows~~.

~~Furthermore, g~~Greenhouse gas (GHG) intensity reductions per unit of~~per kg~~ milk associated with high productivity cows ~~level off~~reduce at high milk yields owing to an increasing share of environmental burden from cultivation, processing and transport of concentrate feed (Gerber *et al* 2011, Mas *et al* 2016), and may be reversed if cropland expansion drives indirect land use change (Styles *et al* 2018). Similarly, although nitrogen emissions factors have generally followed a decreasing trend over the past few decades, intensifying livestock production has in many cases increased total emissions, due to e.g. undesirable losses of reactive nitrogen forms, resulting from the consolidation of farms in specific areas and their disconnect from the croplands where animal feed is produced~~Nitrogen leakage also increases from more intensive systems~~ (Balmford *et al* 2018, Lassaletta *et al* 2016). Also, as~~s~~ dairy farms specialize in milk production and demand for beef increases (Opio *et al* 2013), the reduced dairy-beef output needs to be produced on pure beef systems, typically suckler-beef systems, which are widely adopted in Europe and responsible for 70% of European beef production (Nguyen *et al* 2010, Styles *et al* 2018). Studies show that, when compensating for reduced dairy-beef in suckler-beef systems, higher burdens occur than if dairy-beef output levels were maintained from dairy farms and coupled dairy-beef fattening systems (Soteriades *et al* 2019, Styles *et al* 2018, Vellinga and de Vries 2018). ~~-~~While this is the current direction of intensification, abatement of emissions is possible from the dairy sector without outsourcing input production (Mosnier *et al* 2019). ~~Furthermore, greenhouse gas (GHG) intensity reductions per kg milk associated with high productivity cows level off at high milk yields owing to an increasing share of environmental burden from cultivation, processing and transport of concentrate feed (Gerber et al., 2011; Mas et al., 2016), and may be reversed if cropland expansion drives indirect land use change (Styles et al., 2018). Nitrogen leakage also increases from more intensive systems (Lassaletta et al., 2014; Balmford et al. 2018).~~

Here we explore the b~~B~~alance~~ing~~ of environmental trade-offs between milk and beef production a~~i~~s a complex multiple-criteria decision-making problem ~~that needs to~~ accounting for several outputs across sectors (milk and beef) and burdens at ~~global and local scales~~local, national and international scales (e.g. eutrophication *v*. global warming; Baldini *et al* 2017, Balmford *et al* 2018, Steinfeld *et al* 2006) ~~by weighting, scaling and~~

~~summarizing these factors into holistic indicators of dairy farm environmental performance.~~ In this way, ~~,~~ we ~~can~~ develop, for individual ~~each~~ dairy farms, a single environmental efficiency ratio of aggregated outputs-to-aggregated burdens (known as the 'eco-efficiency' score) that overcomes the disadvantages of partial- and hence by definition simplistic- single-output-to-single-burden life cycle assessment (LCA) ratios (Jan *et al* 2012, Soteriades *et al* 2016). Consequently, trade-offs between burdens may be explored, and the role of dairy-beef production in mitigating burdens may be explicitly modelled, to reveal new insights into the potential of different farm management methods for improving the environmental efficiency of dairy farms.

In the current study, we employed a multiple-criteria decision-making method known as Data Envelopment Analysis (DEA; Cooper *et al* 2007) to measure the eco-efficiency of a detailed representative panel dataset of hundreds of commercial UK dairy farms containing several important farm management variables and burden categories (Soteriades *et al* 2019). One of DEA's virtues is that it uses the data themselves to endogenously weight each variable according to its contribution to the eco-efficiency score, so that (potentially subjective) *a priori* weighting of the variables is unnecessary. However, DEA does not place any restrictions on the weight values. By constraining the weight space in different ways, we developed a set of eco-efficiency permutations to evaluate or propose specific dairy farming pathways relating to (i) increasing milk production intensities or (ii) maintaining a balance between milk and dairy-beef output. ~~That way,~~ Through this approach we aim to inform decision-making in relation to national emissions targets around whether ~~the current ongoing trends on~~ dairy farm intensification ~~(Gonzalez-Mejia *et al* 2018)~~ can deliver more environmentally sustainable milk and dairy-beef production without displacing emissions.

2. Methods

2.1. Data

We used the data of Soteriades *et al* (2019), who developed and applied a method to estimate environmental footprints for a large 15-year panel dataset containing thousands of data points of commercial dairy farms in the UK. This dataset contains 738 (or 3624 data points over 15 years, from 2001/02 to 2015/16) dairy farms taken from the Farm Business Survey, a comprehensive source of business information from farms in England and Wales (FBS 2018, UK Data Service 2018). Using these data, Soteriades *et al* (2019) developed an LCA algorithm that calculated, for each farm in each year, five burdens: global warming potential (GWP, kg CO_2 equivalents; eq.), eutrophication potential (EP, g PO_4 eq., g = 10^{-3} kg), acidification potential (AP, g SO_2 eq.), fossil resource depletion potential (RDP, MJ eq., MJ = 10^6 J) and land occupation (LO, m^2), that we also used in this study. These burdens were estimated using an attributional LCA in accordance with ISO principles (ISO 2006), accounting for upstream impacts associated with the production and transport of inputs and all major animal, manure management and field emissions on the dairy farms (Styles *et al* 2015). The life cycle inventory process followed two earlier LCA studies of UK dairy farms (Styles *et al* 2015, 2018). For assumed emissions from inputs, animals, housing, manure management and application, and fertilizer application, see Table 1 in Soteriades *et al* (Soteriades *et al* 2018a) and section 2.3 in Soteriades *et al* (Soteriades *et al* 2019).

2.2~~1~~. Data Envelopment Analysis

Data Envelopment Analysis is a linear programming-based method that evaluates the performance of decision-making units (DMUs) performing the same task in terms of their ability to convert inputs into outputs (Cooper *et al* 2007). In the context of this study, the DMUs are dairy farms and the task is the production of milk and beef. As mentioned earlier, DEA studies have extended the notion of physical inputs (e.g. land, fertilizers *etc*.) to consider LCA burdens as inputs, so as to measure the performance of DMUs in terms of the potential environmental damage incurred to produce a given output (known as DEA 'eco-efficiency').

The strong advantage of DEA over partial ratios of performance is that it constructs, for each farm, a ratio of the weighted sum of outputs over the weighted sum of burdens. The weights are farm-specific and reflect the relative contribution of each burden and output to the overall efficiency of the farm. The weights are calculated directly from the DEA model, so no subjective assumptions on the importance of each burden and output are required. The weights are applied on the *absolute* levels of the burdens (and outputs), i.e. no allocation of burdens to milk or beef production is necessary. A simple graphical explanation of DEA is provided in the supplementary material.

Combining burdens and outputs with DEA is greatly advantageous for creating overall or 'global' indicators of farm environmental efficiency. Mathematical descriptions of DEA models, their settings and associated theories are comprehensively covered in classic DEA textbooks (Cooper *et al* 2007) as well as in agricultural studies (Jan *et al* 2012, Picazo-Tadeo *et al* 2011, Soteriades *et al* 2016). Extensively discussing models and theories is beyond the scope of our study. However, we do present below the DEA model we used and justify our choice in the supplementary material.

Suppose that there are n DMUs (i.e. dairy farms) each producing m burdens and s outputs, denoted as z_i $(i = 1, \ldots, m)$ and y_r $(r = 1, \ldots, s)$ respectively. Using those burdens and outputs, the DEA model will solve an optimization problem for each farm, in an attempt to obtain the maximum possible DEA efficiency score for that farm, relative to its benchmark(s). Using standard notation of the DEA literature (Cooper *et al* 2007), a DEA model is normally presented for 'DMU$_o$', which represents any of the n DMUs (e.g. the j-th DMU), without loss of generality. The DEA efficiency score of ~~the *j*-th DMU, denoted as~~ DMU$_o$~~,~~ is given by the following fractional programming model:

Model 1:

$$\max_{w_o \cancel{w}, v_o \cancel{v}} \theta_o \cancel{\theta} = \frac{w_{1o}y_{1o} + w_{2o}y_{2o} + \cdots + w_{so}y_{so}}{v_{1o}z_{1o} + v_{2o}z_{2o} + \cdots + v_{mo}z_{mo}}$$

subject to

$$\frac{w_{1o}y_{1j} + w_{2o}y_{2j} + \cdots + w_{so}y_{sj}}{v_{1o}z_{1j} + v_{2o}z_{2j} + \cdots + v_{mo}z_{mj}} \leq 1 \; (j = 1, \ldots, n)$$

$$v_{1o}, v_{2o}, \ldots, v_{mo} \geq 0$$

$$w_{1o}, w_{2o}, \ldots, w_{so} \geq 0.$$

The constraints mean that the ratio of 'virtual output' over 'virtual burden' should be at most one for every DMU. The objective is to obtain weights w_{ro} and v_{io} that maximize the ratio $\theta_o \cancel{\theta}$ of DMU$_o$. Because of the constraints, the optimal objective value θ_o^* $\cancel{\theta^*}$ is at most one for the optimal weights w_{ro}^* and v_{io}^*. See Cooper *et al* (2007, p 23). For a linear programming equivalent of Model 1 and for further interpretations see the supplementary material. See also Camanho and Dyson (2005) for a detailed visual explanation of DEA and Soteriades *et al* (2018b) for a series of practical DEA applications with dairy farms.

2.2~~1~~.1. DEA model setup. We used the two outputs milk (L) and live weight gain (LWG; kg) and the five burdens: GWP, EP, AP, RDP and LO.~~global warming potential (GWP, kg CO_2-equivalents; eq.), eutrophication potential (EP, g PO_4-eq., g = 10^{-3} kg), acidification potential (AP, g SO_2-eq.), fossil resource depletion potential (RDP, MJ eq., MJ = 10^6 J) and land occupation (LO, m^2). See subsection 2.4.~~

2.2~~1~~.2. Constraining the DEA weights. In Model 1, the only restriction on the weights is non-negativity. On the one hand, this allows for considerable flexibility in the selection of the most self-favourable (in terms of maximizing the efficiency ratio) weights values for each DMU, which is one of DEA's most attractive properties (Cooper *et al* 2011). On the other hand, because of this property, situations can arise where many DMUs have zero weights in most variables and non-zero weights in only a few remaining variables (Theodoridis and Ragkos 2015)[1]. When the DEA practitioner deems a variable with a trivial weight to be important, then it should be retained and the DEA model should be modified to ensure that the variable receives a non-trivial weight (Pedraja-Chaparro *et al* 1997).

There are several methods for constraining the weights in Model 1 that are extensively covered in the literature (Cooper *et al* 2007, 2011). In this study, we chose the so-called Assurance Regions of type I (AR-I; Cooper *et al* 2011):

AR-I:

$$L_{1i} \leq \frac{v_{io}}{v_{1o}} \leq U_{1i}, i = 2, \dots, m$$

$$l_{1r} \leq \frac{w_{ro}}{w_{1o}} \leq u_{1r}, r = 2, \dots, s,$$

where L_{1i} and U_{1i} are the user-defined lower and upper bounds, respectively, for the burden weights ratios. The subscript '$1i$' denotes that the bounds for burdens $2, \dots, m$ are expressed with reference to burden 1. Similarly, l_{1r} and u_{1r} are the user-defined lower and upper bounds, respectively, for the output weights ratios. The subscript '$1r$' denotes that the bounds for outputs $2, \dots, s$ are expressed with reference to output 1. These AR-I inequalities were added to the constraints of Model 1.

2.2~~1~~.3. Defining bounds for the assurance regions. The use of assurance regions stems from the very practical challenge of getting the DEA model to prioritize the treatment of variables (here outputs and burdens) in a way that reflects the user goal, without biasing the model. It is our viewpoint that the DEA model cannot be allowed to give too much weight to milk and trivial weight to LWG knowing that such an unbalanced set of optimal weights would completely disregard the fact that dairy-beef is a co-product of milk production. It is this very co-product that needs to be explicitly considered for assessing the true environmental and beef-supply implications of dairy farming specialization (Soteriades *et al* 2019). In a similar way of thinking, GWP is only one of the numerous significant environmental impacts of dairy farming, so the contribution of burdens other than GWP to the DEA eco-efficiency scores should not be masked by large weights for GWP and small weights for the other burdens. Indeed, trial runs resulted in most farms receiving a very high weight for GWP and zero

[1] This was indeed the case with our model and data: trial runs resulted in most farms receiving a very high weight for GWP and zero or near-zero weights for the other four burdens.

or near-zero weights for the other four burdens, which is like saying that EP, AP, RDP and LO were not at all important in estimating dairy farm environmental efficiency.

However, there is no theoretical framework with which weights bounds may be defined. Some DEA practitioners use data-based methods to avoid introducing subjectivity to the definition of the bounds. For instance, one may use price data, when they are available, or apply statistical modelling such as regression to obtain model-based bounds using the available physical data (Cooper *et al* 2011, Theodoridis and Ragkos 2015). Alternatively, bounds can be defined by domain experts working with DEA practitioners in assessing the performance of DMUs in a specific industry (Cooper *et al* 2009).

Given range of methods and the challenge of ~~As the AR-I bounds are user-defined, there are numerous ways of defining them, based on the available information (e.g. price data), expert knowledge or modelling methods (Cooper *et al* 2011, Theodoridis and Ragkos 2015). We~~ defining~~ed~~ the AR-I bounds as objectively as possible in our study, we used a combination of simple data-based approaches and subjective decisions, accompained by a series of scenario permutations in an effort to be as comprehensive as possible. The AR-I bounds were defined and justified as follows:

- Burdens: We explored the effect of different weighting on burdens by setting $L_{1i} = 0.5$ and $U_{1i} = 1.5$ in all AR-I inequalities, i.e. we considered that EP, AP, RDP and LO were at least half to 1.5 times as important as GWP. We then increased the importance of these four burdens relative to GWP by performing additional runs with $L_{1i} = 0.9$ and $U_{1i} = 1.1$ and finally with $L_{1i} = U_{1i} = 1$ (i.e. all burdens equally weighted). The choice of ranges is entirely empirically determined. The rationale is that we want to (i) on the one hand, allow the weights to move as freely as possible, yet within reasonable constraints (a range of 0.5 to 1.5 is already quite wide); and (ii) on the other hand, ensure that we are not unjustifiably assigning too low and/or too high weights to particular burdens.
- Outputs: (i) Given the various sets of bounds for the burdens, we first considered a more extreme case where milk production was by far more important than beef production. We therefore set the AR-I output bounds according to the contribution of gross energy (GE) from LWG (assuming 12.56 MJ kg^{-1} LWG) relative to GE from milk (assuming 2.5 MJ L^{-1}) in each dairy farm (Styles *et al* 2015). Depending on the year, the ratio GE from LWG-to-GE from milk ranged between 0.04 and 0.7 in the data, with a mean and standard deviation of 0.16 and 0.05 respectively. We will refer to this set of models as *DEA-milk focussed*, because energy ratios emphasize the dominance of milk as an output. (ii) Then, we increased the importance of LWG relative to milk by setting $l_{12} = 0.5$ and $u_{12} = 1.5$ and finally $l_{12} = u_{12} = 1$. We will

refer to this collection of models as *DEA-milk & beef*. In this manner, we obtained two sets of DEA models that represent two distinct dairy farming pathways for improving environmental performance: (i) increasing milk efficiencies (*DEA-milk focussed*); and (ii) recognizing the role of dairy-beef in mitigating burdens (*DEA-milk & beef*; Soteriades *et al* 2019).

We considered all combinations of the aforementioned weights values for the burdens and outputs, resulting in 36 permutations for *DEA-milk & beef* (two sets of values for L_{1i} × three sets of values for U_{1i} × two sets of values for l_{12} × two sets of values for u_{12}) and in nine permutations for *DEA-milk focussed* (three sets of values for L_{1i} × three sets of values for U_{1i}).

It should be noted that we ran *DEA-milk & beef* by first dividing all outputs and burdens by their standard deviations. By making outputs and burdens dimensionless, our weights restrictions can be straightforwardly interpreted as 'burden (or output) *A* is *X* times as important as burden (or output) *B*'. In other words, by dividing by the standard deviation any proportional changes in the measurement units (e.g. from g to kg) have no effect on the interpretations of the AR-I restrictions. Conversely, because in *DEA-milk focussed* the output bounds were determined by the GE shares of LWG and milk, we converted these two outputs into their corresponding amounts of GE and did not divide by their standard deviations before running this set of DEA models.

2.2~~1~~.4. Decomposing DEA eco-efficiency. In addition to its ability to construct global eco-efficiency indicators, an additional advantage of DEA is that it can indicate the variables that contribute the most to a farm's inefficient performance (if any). This is done by calculating, for each inefficient farm, output and burden inefficiencies (or 'slacks' in the DEA terminology), that is, output shortfalls and burden excesses. In more detail, an inefficient farm is inefficient because it generates more burdens and/or produces less outputs than its benchmarks. Such a farm can become eco-efficient once it has increased its outputs and/or reduced its burdens by their corresponding slacks.

Studies typically divide the slacks by their corresponding variables to identify the variables with the highest relative contributions to a farm's inefficient behaviour (Cooper *et al* 2009). We here take an alternative approach by harnessing a property that DEA models exhibit only when AR constraints are added to them: slacks can also take negative values[2]. Negative slack in a variable indicates that a farm exceeds the values considered as efficient for this farm in this variable, relative to its benchmark farm(s) (Cooper *et al* 2009). We plotted, for each year, variable (outputs and burdens), scenario and permutation, the number of negative slacks as opposed to the number of positive slacks. We also plotted the proportion of positive slacks in inefficient DMUs across all

[2] Without the AR constraints, slacks are semi-positive. We present the formulas for calculating slacks in DEA models with AR constraints in the supplementary material.

years and permutations for each scenario. These plots helped to identify patterns of (in)efficient behaviour in each output and burden. In this way we obtained a more holistic overview of the farms' eco-efficiency performance.

2.3~~2~~. Explaining eco-efficiency: Generalized Additive Model

We used a generalized additive model (GAM) to explore the effect of dairy farm intensification at the animal- and farm-levels on dairy farm environmental performance.

The GAM provides a general statistical framework for modelling the interaction between a predictor variable and a set of explanatory variables. Its data-driven, non-parametric, nature makes GAM a more flexible tool than traditional parametric modelling (Hayn *et al* 2009). The linear predictor depends linearly on smooth functions of predictor variables and the assumption that the response is normally distributed is relaxed by allowing it to follow any distribution from the exponential family (Wood 2017). Importantly, GAM is able to fit a flexible functional form to determine the relationship between the response and each predictor variable (Hayn *et al* 2009).

We ran 45 GAMs with the DEA eco-efficiency scores from each permutation as the dependent variable and a number of independent variables, described as follows:

- Animal-level intensity variables: milk:beef ratio (L milk/g LWG); milk/cow (L/cow); concentrate consumption (t concentrate DMI/LU); and concentrate:milk ratio (t concentrate DMI/L milk).
- Farm-level intensity variables: stocking rate (LU/ha); and milk/forage area (L/ha).
- Control variables: dairy cows (average number in the farming year); forage area (ha); and region (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, South East, South West, and Wales).
- Year variables: dummy variables for the years 2001–2015.

All numeric predictor variables had long-tailed distributions and so were log-transformed (Hastie *et al* 2017, p 301).

2.4~~3~~. Correlated predictors and variable selection

Before turning to the GAM and DEA results, we note that we had to reduce the number of predictors in the GAM model, owing to correlated predictors. In GAMs, correlated predictors can cause concurvity, which can be viewed as a generalization of multicollinearity in linear models and can thus cause similar problems of interpretation (Wood 2019).

Many pairs of predictors were moderately to highly correlated. This naturally resulted in moderate/high concurvity values for all smooth terms in our GAM models[3], consequently raising a few issues regarding the interpretation of the results.

A particularly problematic interpretation was for the stocking rate: preliminary runs suggested that its relationship with eco-efficiency was negative, while the relationship between eco-efficiency and (i) number of dairy cows; and (ii) the forage area, were positive and negative respectively (Figure 1[4]). If anything, increasing the number of dairy cows at average forage area levels or, conversely, reducing the forage area at mean dairy cow levels, should imply increasing stocking rates. The unexpected negative sign for stocking rates (Figure 1) was not easy to interpret- especially when controlling for so many (correlated) predictors- and may as well have been wrong for several modelling reasons discussed in detail in Kennedy (2005).

[3] We calculated ‘estimate’ concurvity with R function ‘concurvity’ in package ‘mgcv’ (Wood 2019, 2017).
[4] The interpretations from Figure 1 were similar for all 45 permutations. The partial residuals displayed on the plots are commented on later.

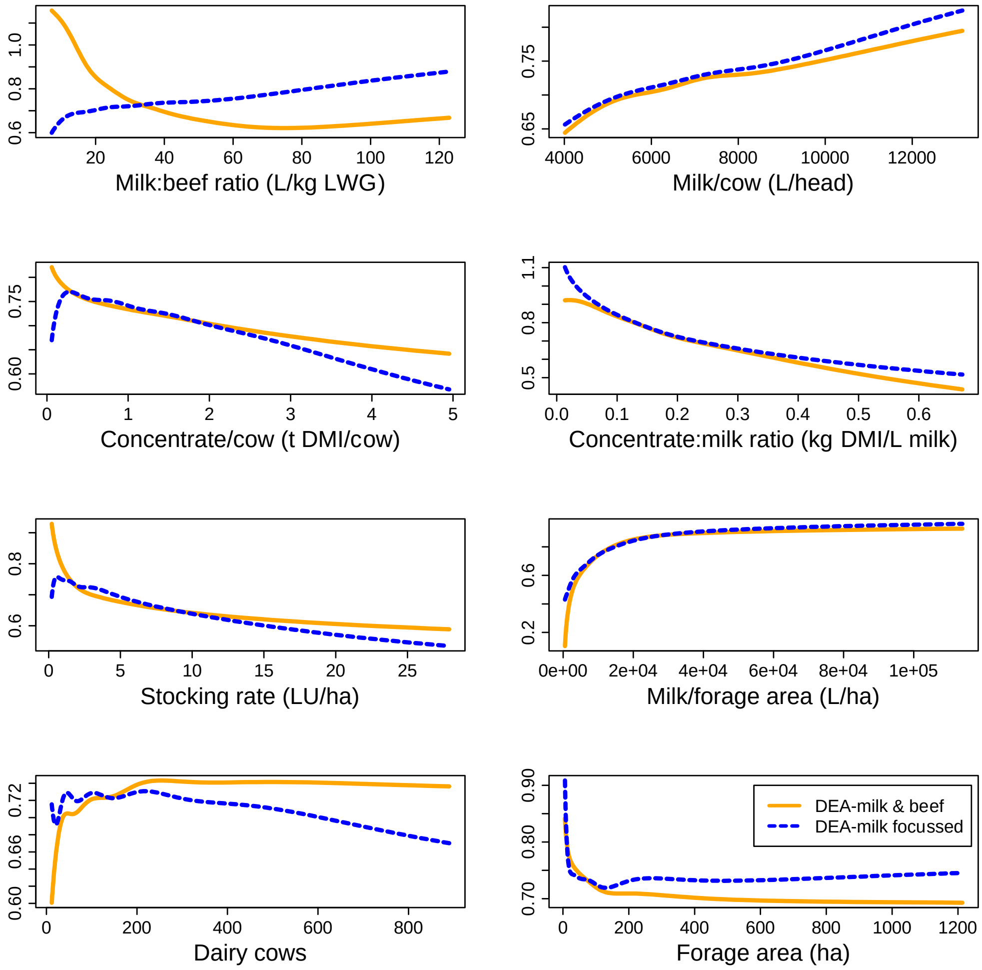

Figure 1. GAM regression results with DEA eco-efficiency as the dependent variable for *DEA-milk & beef* (DEA model with and $(L_i, U_i) = (l_2, u_2) = (0.5, 1.5)$) and *DEA-milk focussed* ($(L_i, U_i) = (0.5, 1.5)$; (l_i, u_i) was year-specific and ranged between 0.04 and 0.7 across all years). Points on the plots are partial residuals.

To control for these problems, we used Lasso regression to study the behaviour of the regression coefficients. Briefly, Lasso is a shrinkage method in regression by which only a subset of predictors is retained, possibly leading to a model with a lower prediction error (Hastie *et al* 2017). Lasso introduces a penalty to the least squares minimization problem that shrinks to zero the coefficients of the predictors to be discarded. This penalty is controlled by a lambda variable that can be estimated with cross-validation. We ran a Lasso for each of the 45 permutations, where the lambda parameter was determined by 10-fold cross-validation~~ with R package 'biglasso' (Zheng and Breheny 2019)~~. According to Lasso, coefficients for stocking rates for all 45 runs were positive (Figure 2), contrary to what was observed for the GAM models (Figure 1). Additionally, the sign of the coefficients for concentrate consumption was inconsistent in the Lasso (Figure 2), contrasting with GAM model results (Figure 1). Finally, in many permutations the coefficients for concentrate consumption were zero (Figure 2), indicating that this variable should be removed from the corresponding GAM models. We therefore decided to remove stocking rates and concentrate consumption from the predictor set.

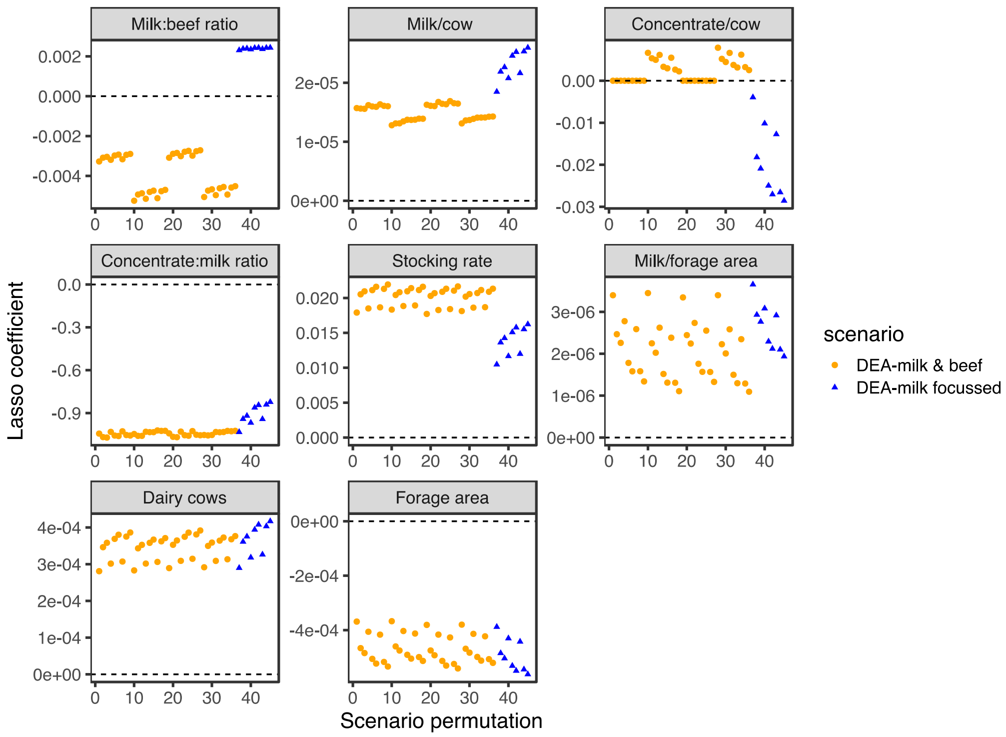

Figure 2. Lasso coefficients for all 45 scenario permutations for scenarios *DEA-milk & beef* (36 permutations) and *DEA-milk focussed* (nine permutations).

~~*2.4. Data*~~

~~*We used the data of Soteriades et al (2019), who developed and applied a method to estimate environmental footprints for a large 15-year panel dataset containing thousands of data points of commercial dairy farms in the UK. This dataset contains 738 (or 3624 data points over 15 years, from 2001/02 to 2015/16) dairy farms taken from the Farm Business Survey, a comprehensive source of business information from farms in England and Wales (FBS 2018). Using these data, Soteriades et al (2019) developed a LCA algorithm that calculated, for each farm in each year, the five aforementioned burdens (GWP, EP, AP, RDP and LO) that we also used in this study.*~~

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2.5. Software

All calculations were performed in the R programming language (R Core Team 2020). The DEA model was run with a tailor-made function available for download from GitHub (Soteriades 2020). The GAM and Lasso models were run with R packages ‘mgcv’ (Wood 2019, 2017) and ‘biglasso’ (Zheng and Breheny 2019) respectively. Visualizations were performed with both R’s built-in graphics functions as well as with package ‘ggplot2’ (Wickham 2016). The residuals of the GAM models in Figure 1 were calculated with package ‘visreg’ (Breheny and Burchett 2020).

3. Results and discussion

3.1. Effects of dairy farm intensification on eco-efficiency

Figure 3 shows the regression lines for all 45 permutations (36 for *DEA-milk & beef* and 9 for *DEA-milk focussed*) after removing stocking rate and concentrate consumption from the predictor set[5]. For clarity, partial residuals were not plotted, however the residuals in Figure 2 are representative of model fit for all 45 permutations.

For all *DEA-milk & beef* and *DEA-milk focussed* models, eco-efficiency increased with increasing milk/cow and milk/forage area; and decreased when the concentrate:milk ratio and forage area increased (Figure 3). Moreover, there was a positive relationship between number of dairy cows and eco-efficiency in general, although for some *DEA-milk focussed* permutations eco-efficiency slightly decreased at higher dairy cow numbers (Figure 3). These small decreases were possibly a result of points with high leverage (farms with larger dairy herds) ‘pulling down’ the regression line (Figure 2). In fact, the interpretations for variables dairy cows and forage area were reversed at very high outlier values (Figures 2–3). However, outliers in these two variables were comparatively few relative to the main cloud of residuals (Figure 2), so we recommend interpreting the reversed slopes of the regression lines for high-leverage points as being unsatisfactory model fits (note more scattered residuals in Figure 2), rather than attempting to provide a physical explanation of these fits for larger values.

[5] Proportion of deviance explained ranged between 68% and 82%. The *p*-values of the parametric and smooth terms ranged between 0 and 0.041, and between 0 and 0.014 respectively.

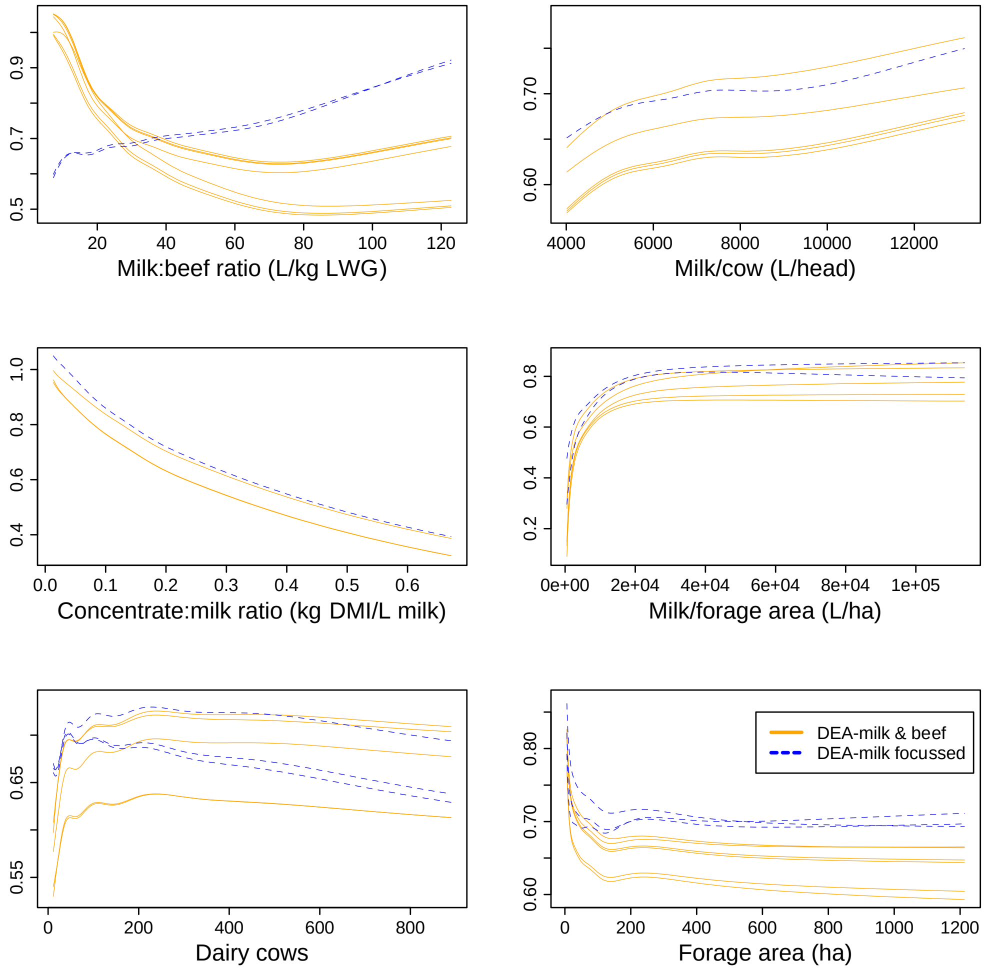


Figure 3. Final GAM regression results with DEA eco-efficiency as the dependent variable for *DEA-milk & beef* (36 permutations) and *DEA-milk focussed* (nine permutations).

Our findings (Figure 3) highlight that efficient use of concentrates improves the eco-efficiency of dairy farms. This is evident from the negative relationship between the eco-efficiency and the concentrate:milk ratio. Several studies show that concentrates play a central role in increasing cow productivity as they contain more digestible energy per kg~~unit~~ of dry matter intake, thus reducing GWP/L (Capper *et al* 2009, Hristov *et al* 2013). However, concentrate:milk refers not only to the amount of concentrate fed but to feed utilization efficiency: the highest milk yield per unit of concentrate fed. This has been strongly supported in the literature (Bell *et al* 2011, Yan *et al* 2010). The current study extends these findings beyond GWP/L by demonstrating a positive relationship between our more comprehensive eco-efficiency indicator and animal-level intensification.

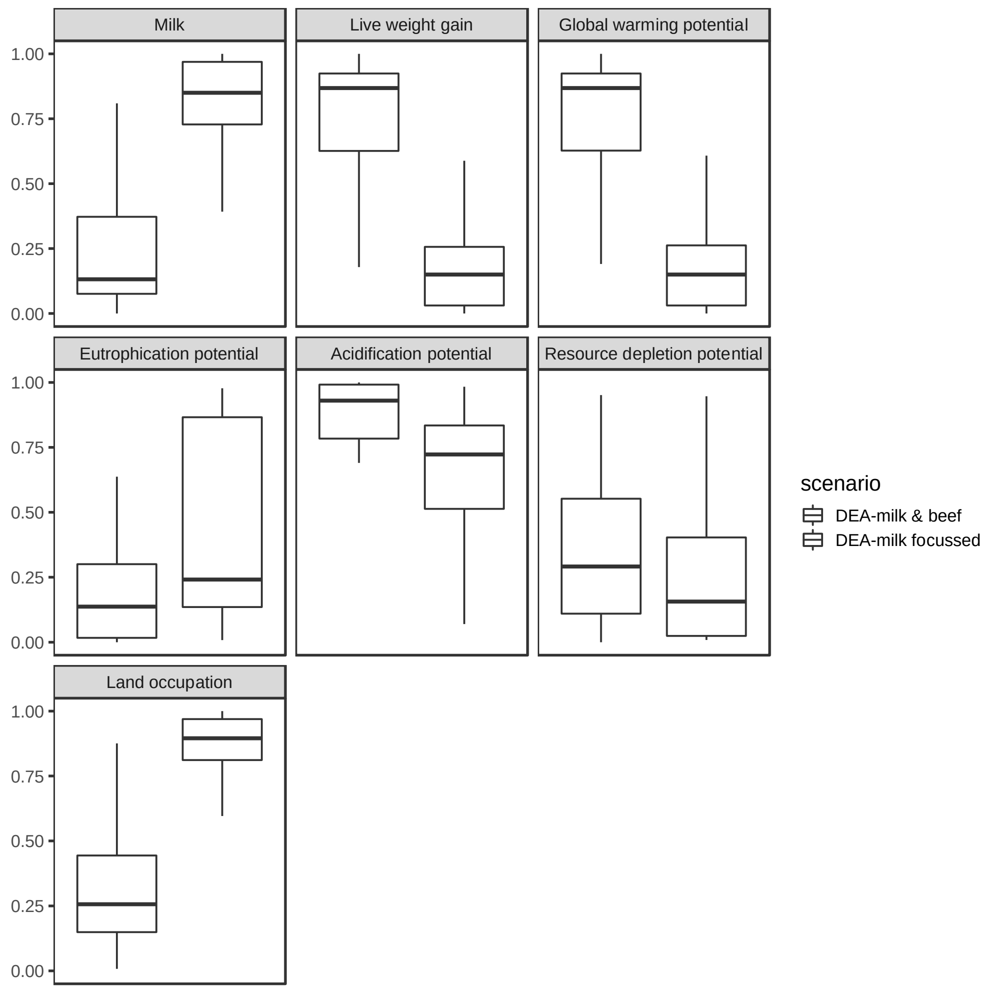
Our findings for farm-level intensification strategies using our more holistic DEA eco-efficiency indicator extend Basset-Mens *et al* (2009), who found that dairy farming systems with higher intensities in terms of stocking rates and milk/forage area achieved smaller ~~lower levels of~~ GWP, EP, AP, RDP and LO burdens per L. Indeed, Figure 3 demonstrates a positive relationship between eco-efficiency and milk/forage area. The latter variable is not only an indicator of intensification but also of feed utilization efficiency since better quality forage may result in increased milk production (Moorby *et al* 2016, Soteriades *et al* 2018a). A positive relationship between eco-efficiency and stocking rate is implicit in the same figure, because, all else held at average levels, increasing dairy cows and reducing the forage area positively and negatively impacted on eco-efficiency, respectively.

Finally, farm size in terms of area has a generally negative effect and herd size a generally positive effect on eco-efficiency (Figure 3). Dairy farms with larger forage areas tend to be less efficient in milk production owing to their more extensive nature, while farms with larger dairy herds represent consolidated and intensified farms that benefit from greater efficiencies of production (Gonzalez-Mejia *et al* 2018).

3.2. Trade-offs between milk and dairy-beef production

The contrasting results between *DEA-milk & beef* and *DEA-milk focussed* for the milk:beef ratio (Figure 3) emphasise that different farm management approaches aimed at burden mitigation can result in significant trade-offs in dairy farm environmental performance. Although our findings suggest that higher milk yields per cow and per ha, as well as more efficient concentrate use, can improve eco-efficiency (Figure 3), we demonstrate, in the top-left panel of Figure 3, that solely focussing on increasing milk production efficiencies can seriously underestimate the role of dairy-beef in estimating eco-efficiency (Soteriades *et al* 2019). Indeed, because DEA is designed to calculate the most self-favourable weights that will maximize the eco-efficiency of the farm under evaluation, models *DEA-milk focussed* assigned larger weights to milk relative to LWG. This is expected given that dairy farms have been increasing milk yields per cow over the past decades (Gonzalez-Mejia *et al* 2018). Consequently, less focus has been placed on maintaining or increasing the levels of dairy-beef production. As a result, there are environmental efficiency losses that models *DEA-milk & beef* were able to reveal.

The signs of the output slacks further illuminate the trade-off between milk and dairy-beef production (Figures 4, S2–S3). Under model *DEA-milk focussed*, milk slacks were generally positive and LWG slacks were negative in most years, and the opposite trends were generally observed for *DEA-milk & beef*. These results indicate that the benchmarks of inefficient farms are much more oriented towards milk than LWG production for *DEA-milk focussed*, while the contrary was true for *DEA-milk & beef*. This is because under *DEA-milk focussed* inefficient farms exceeded the performance of their referent farms in aspects *other* than milk, that is, in LWG. On the other hand, *DEA-milk & beef* inefficient farms exceeded the performance of their referent farms in aspects *other* than LWG, that is, milk. Indeed, median values[6] for milk/cow and the milk:beef ratio of benchmark and inefficient dairy farms for *DEA-milk focussed* (similarly, under model *DEA-milk & beef*) were 7934 L/head and 45 L/kg LWG and 7060 L/head and 35 L/kg LWG respectively (6140 L/head and 23 L/kg LWG and 7078 L/head and 34 L/kg LWG respectively).



[6] Here median values are presented across all years. However, similar patterns for medians were observed within individual years.

Figure 4. Summary of the proportion of positive slacks (output slacks: shortfalls relative to benchmark(s); burden slacks: excesses relative to benchmark(s)) of inefficient farms in the 45 permutations of models *DEA-milk & beef* (36 permutations; boxplots on the left-hand side) and *DEA-milk focussed* (nine permutations; boxplots on the right-hand side).

3.3. Trade-offs between burdens

The signs of the burden slacks (Figures 4, S2–S3) show that, under both *DEA-milk focussed* and *DEA-milk & beef*, inefficient farms were inefficient in AP in most years (positive slacks), while they generally exceeded the performance of their benchmarks in terms of RDP (negative slacks). The GWP slacks of inefficient farms were negative for *DEA-milk focussed* and positive for *DEA-milk & beef*, while the opposite pattern was true for the LO slacks. The EP slacks were mostly negative for *DEA-milk & beef* (Figures 4, S3). The EP slacks for *DEA-milk focussed* were slightly more varied in sign: they were mostly negative in the majority of years and permutations, but in five years the proportions were more than 70% positive in all nine permutations (Figures 4, S2).

The signs of the GWP slacks constitute an interesting finding. In particular, they show that less milk-intensive farms are more efficient in GWP than farms that are more focussed on increasing milk production efficiencies. In other words, although improvements in feeding and manure management have generally reduced GWP per L (Capper *et al* 2009), our findings show that *absolute* levels of GWP are generally lower for less milk-balanced farms, i.e. increasing milk production intensities increases the amount of carbon dioxide equivalents released into the atmosphere. However, this is compensated by the fact that the absolute levels of LO drop in more milk-intensive dairy farms, and there is some evidence that the same is true for the absolute levels of EP (Figures 3–4, S2–S3).

By contrast, consistently negative and positive outcomes are observed for the RDP and AP slacks respectively (Figures 4, S2–S3). This means that dairy farms, regardless of their degree of specialization in milk production, urgently need to prioritize the reduction of AP, through strategies that minimize emissions from grazing, manure management and soils. At the same time, although our DEA models indicate that improving RDP efficiencies are not a priority for increasing eco-efficiency in the DEA models, the magnitudes of RDP slacks could be further reduced through more efficient use of imported feeds and fertilizers.

3.4. ~~Methodology~~Comparisons with earlier studies

This study contributes to a relatively recent stream of carbon foot-printing/LCA literature that argues that the analysis of the environmental impacts of dairy farming needs to explicitly account for interrelations between milk and beef production (Flysjö *et al* 2012, Soteriades *et al* 2019, Styles *et al* 2018, Vellinga and de Vries 2018, Zehetmeier *et al* 2012). These studies have used different modelling approaches, scenario analyses, datasets and modelled production systems to reach similar conclusions. In more detail, Flysjö *et al* (2012) used a 'system expansion' method to avoid allocation of dairy farm burdens to milk only, by expanding system boundaries to include functions related to co-products. Applying their method on 23 Swedish dairy farms, they concluded that increasing milk yields does not necessarily lead to lower carbon dioxide levels for milk, because dairy farms with high meat production can offset carbon dioxide from avoided beef production in less climate friendly cow-calf systems. Similar conclusions were made by Zehetmeier *et al* (2012) for scenario-based modelling analyses of typical German production systems. Styles *et al* (2018) expanded these findings by quantifying the land use change impacts on carbon footprints that increasing milk yield per cow can have when shifting a UK dairy system from average to high milk-producing intensity, as a greater area of land for beef production would be required to counterbalance reduced dairy-beef production. Similarly, Vellinga and de Vries (2018) showed that typical climate change mitigation strategies other than increasing milk yield per cow can also be less effective in reducing carbon footprints in Dutch systems, owing to losses in dairy-beef production levels. Finally, Soteriades *et al* (2019) expanded the study of Vellinga and de Vries (2018) by including more burdens (GWP, EP, AP, RDP and LO) and using a 15-year panel dataset of the 738 commercial dairy farms also studied here, to conclude that burdens per unit of milk could be reduced by 11—56% when more dairy-beef is produced per unit of milk produced on a dairy farm.

The results of the current study are in broad agreement with these earlier exercises, although from a couple of alternative and advantageous viewpoints. First, instead of examining 'what-if' scenarios of modelled farms (as in Styles *et al* 2018, Vellinga and de Vries 2018, and Zehetmeier *et al* 2012), DEA helps evaluate 'what has happened' based on available data on past production of *actual* farms. Second, with DEA it is easier to handle the numerous burdens and production outputs that are typically involved in agricultural production. As noted earlier, a strong advantage of DEA is that it weights outputs and burdens according their contribution to the overall efficiency of a farm relative to its benchmark(s). ~~Alternative methods have been used in LCA studies for weighting/normalizing LCA indicators in order to aggregate or compare the contribution of different burden categories (e.g. Meul *et al* 2014).~~ We ~~however~~ therefore advocate for the use of DEA as a means of (i) minimizing the influence of subjectivity from the weighting process[7]; (ii) identifying and accounting for each

[7] It may be claimed that this argument is invalidated in our study owing to our decision to constrain the DEA weights space. It must be noted that constrained weighting *still* allowed weights to move freely- although within limits that helped us develop scenario permutations for making insightful comparisons.

farm's 'uniqueness' in the sense that they may be inefficient in *different* areas than other farms; and (iii) accounting for several outputs simultaneously in the eco-efficiency ratio (in this case, milk and LWG), rather than allocating burdens to a single product.

It is worth mentioning that there exist alternative methods for developing more holistic performance indicators for (dairy) farms. For example, Vellinga and de Vries (2018), and subsequently Soteriades *et al* (2019), expressed LCA burdens per a 'complex' functional unit that represented a fixed volume of milk *and* beef output for each farm. On the other hand, although Meul *et al* (2014) did not account for beef produced in the calculated burdens, they used LCA in a novel way, that is, as a decision-support tool for dairy farmers in Belgium, using a normalization process that assigned a bounded score of relative importance to each burden (expressed per unit of milk produced). These relative burden scores helped identify farm-specific strategies for optimizing farm management and reducing burdens. By contrast, Hassani *et al* (2019) resorted to advanced mathematical and computer modelling to develop a resilience and sustainability indicator for Iranian dairy farms, by integrating environmental, economic, social, technology and policy indices. Interestingly, by introducing the resilience aspect in their indicator, they considered unpredictable events such as price fluctuations and volatility in government subsidies.

Explicitly modelling unpredictable events and random shocks is becoming increasingly important considering global population growth and changing patterns of weather variability because of climate change. A recent study found that uncertainty requires more land to be converted into agricultural use as a hedge against production shortages (Lanz *et al* 2017). This may negatively impact on the farm environmental efficiency, for example in relation to LO for crops. A further methodological development of this study could therefore be to account for such uncertainties in the calculating burdens and DEA scores.~~Alternative methods have been used in LCA studies for weighting/normalizing LCA indicators in order to aggregate or compare the contribution of different burden categories (e.g. Meul *et al* 2014).~~ ~~It may be claimed that argument (i) above is invalidated in our study owing to our decision to constrain the DEA weights space. It must be noted that constrained weighting *still* allowed weights to move freely, although within limits that helped us develop scenario permutations for making insightful comparisons.~~

4. Conclusion

Our development of multiple-criteria decision-making models and scenario permutations reflecting the importance of milk and beef production for the eco-efficiency of dairy farms provided several important

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insights. Our main finding, across a large panel of farms, is that the role of dairy-beef in improving the eco-efficiency of dairy farms should not be underestimated. In other words, solely focussing on improving milk production efficiencies provides a one-sided approach to the problem of improving the environmental sustainability of dairy farms, and in particular the ruminant food systems they are integral to. Our results also show that increasing feed conversion efficiencies has a positive effect on eco-efficiency, and so does herd size. Our scenario permutations revealed a significant trade-off between global warming potential and land occupation: less milk focussed farms need to prioritize reduction of land occupation (i.e. use land more efficiently), whilst more milk focussed farms need to prioritize reduction of GHG emissions. On the other hand, farms were generally consistently inefficient in AP, highlighting the importance of grazing management, manure and soil management for reducing this potent local impact. We conclude that our multiple-criteria decision-making shows that intensification of dairy farming may not necessarily deliver more environmentally sustainable milk and dairy-beef production, owing to the significant ~~production and~~ indirect environmental trade-offs associated with reduced dairy-beef production. This finding should be taken into account when assessing environmental policies at the national level especially when these require no displacement of emissions overseas or between sectors.

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Figure 1

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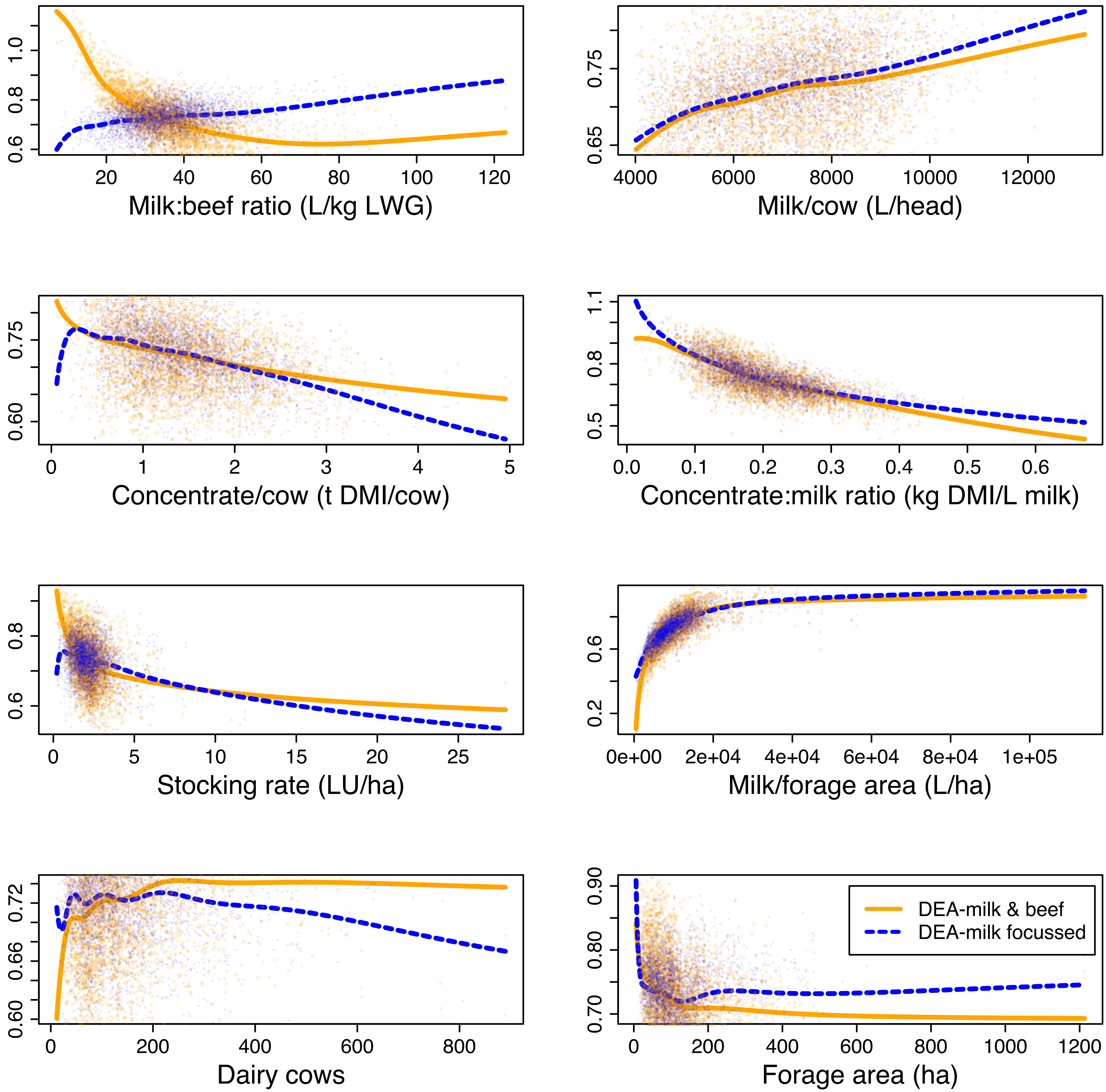

Figure 2
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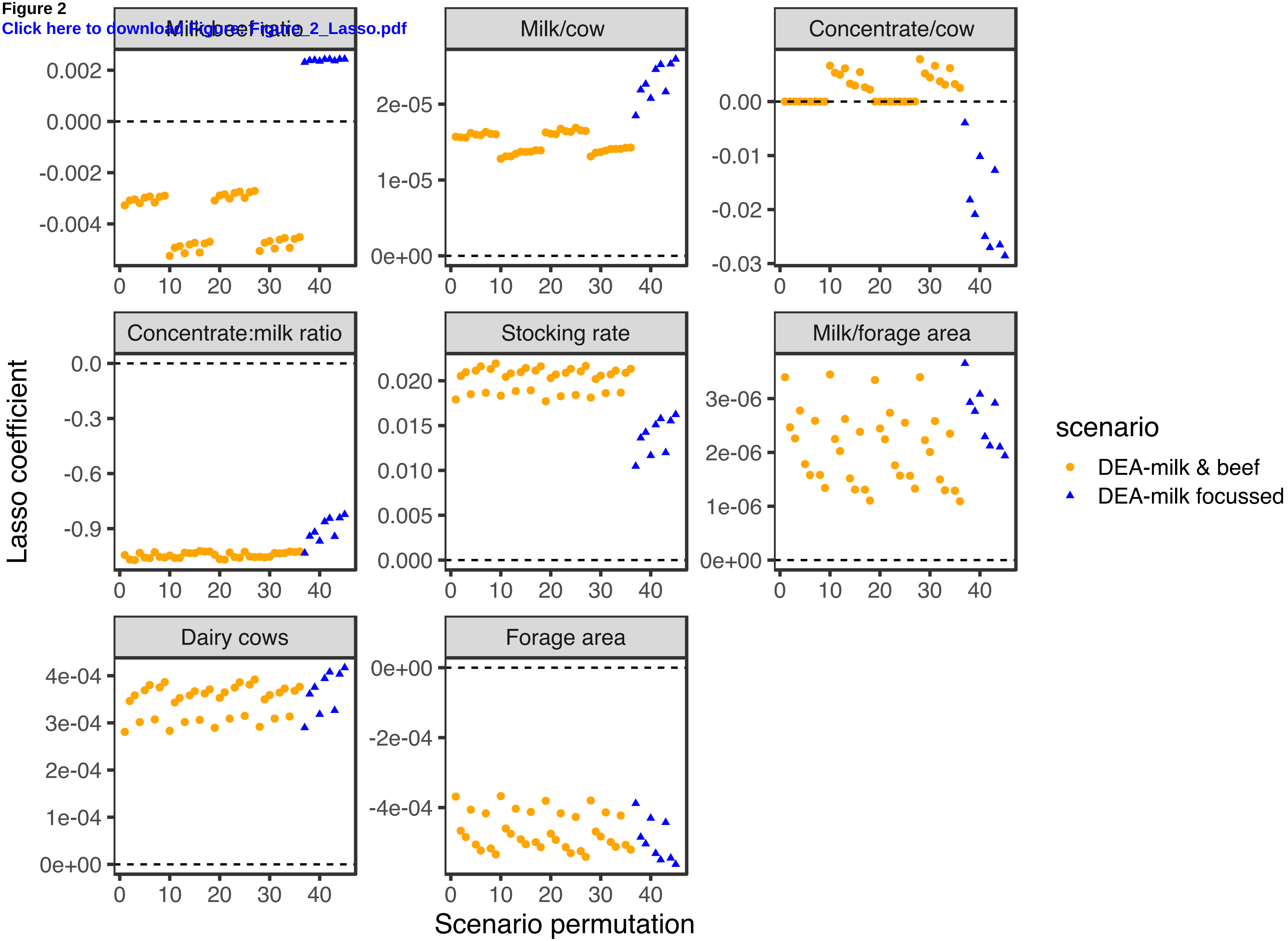

Figure 3

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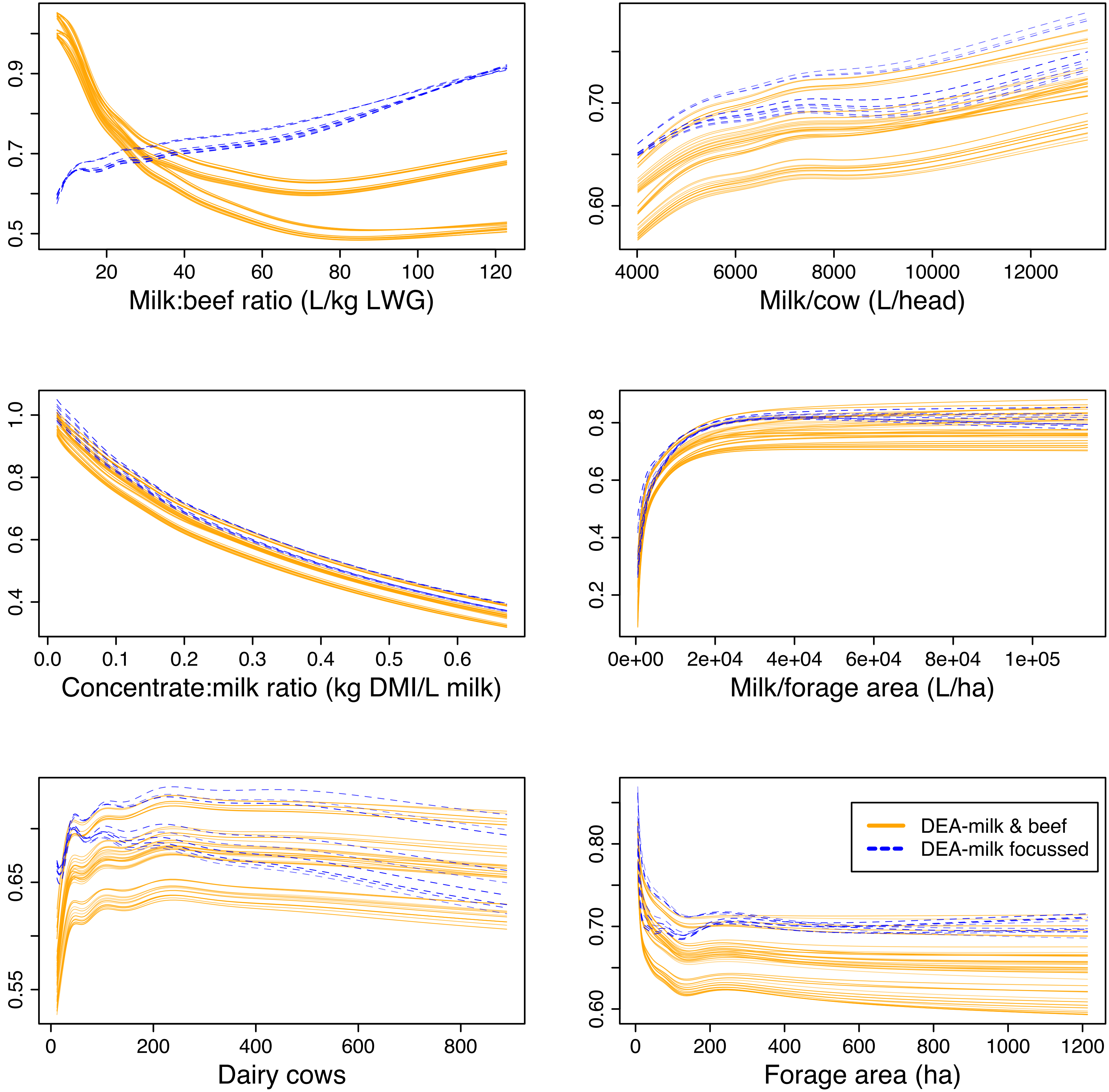

Figure 4

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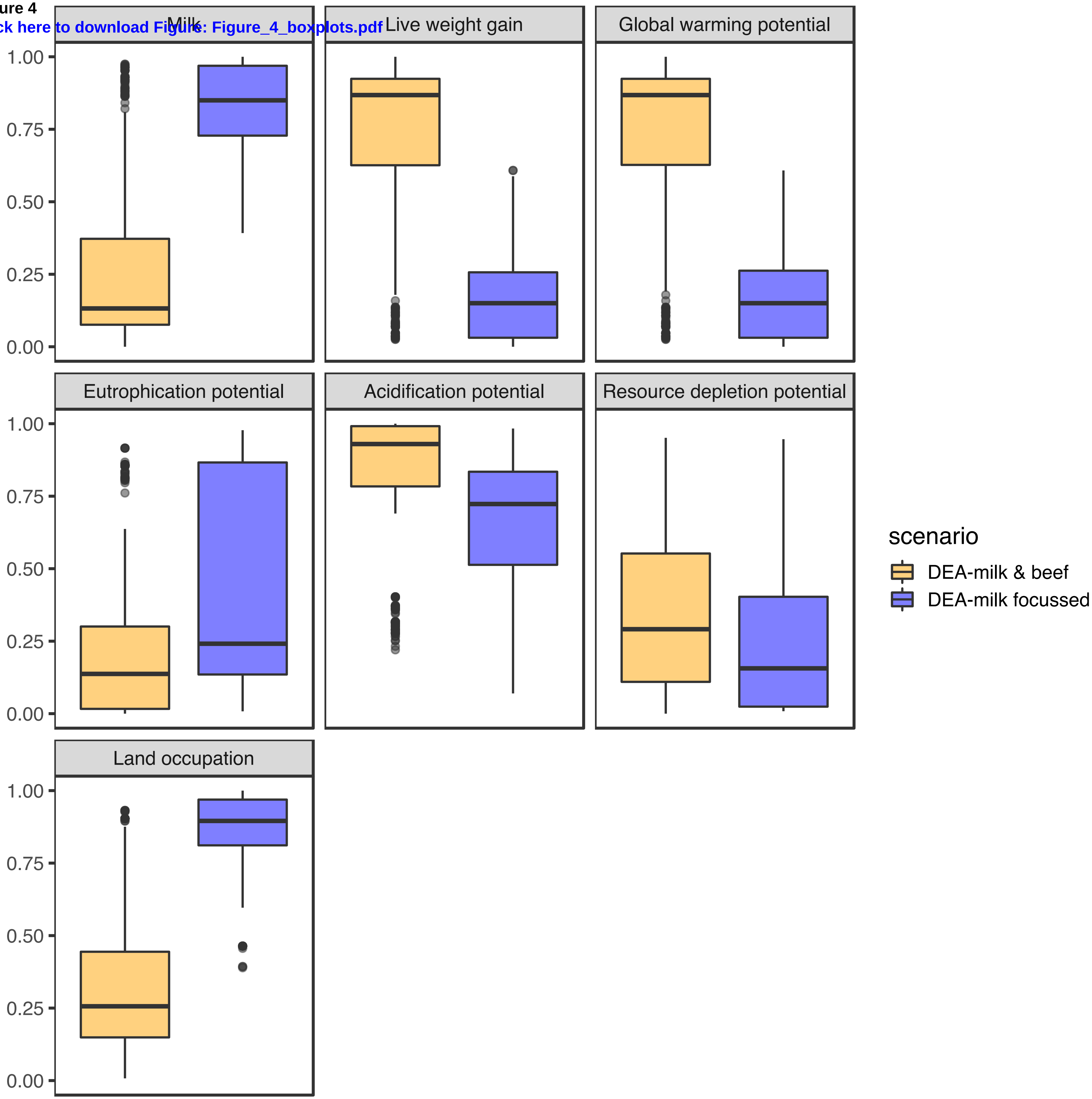

Supplementary Material

Table of Contents

Data Envelopment Analysis

The virtues of DEA in can be better understood by graphically explaining the method. In more detail, DEA constructs an efficient frontier consisting of the best performers in the sample and all other farms are benchmarked against this frontier. The two-dimensional frontier illustrated in Figure S1 represents a simple case where each of the five farms A to E produces two burdens (z_1 and z_2) and one output (y). In this example, the output is normalized to unity. Farms on the southwest of the plot (farms A to D) produce the lowest amounts of z_1 and z_2 for their levels of y, so they are the best performers. They therefore form the piece-wise linear frontier ABCD against which farm E is benchmarked. Farms A to D are deemed 100% efficient by DEA and are assigned a score of one. Farm E is inefficient and is assigned a semipositive score strictly less than one, indicating how 'far' this farm is from achieving 100% efficiency. Efficiency is attained by proportionally reducing z_1 and z_2 for farm E until it reaches the frontier on point R_{BC}. Mathematically, this is done by solving a linear program in which the ratio of the weighted sum of outputs over the weighted sum of burdens is maximized for farm E (this ratio is the DEA score of farm E). In this example, the ratio is y_E / ($v_{1,E}$ $z_{1,E}$ + $v_{2,E}$ $z_{2,E}$), but in the general case with n farms producing m burdens and s outputs it is ($w_{1,j}$ $y_{1,j}$ +…+ $w_{s,j}$ $y_{s,j}$) / ($v_{1,j}$ $z_{1,j}$ +…+ $v_{m,j}$ $z_{m,j}$), j = 1,…n, where $v_{M,j}$ and $w_{S,j}$ (M = 1,…m, S = 1,…s) are farm-specific weights reflecting each burden's and output's relative contribution to the overall efficiency of the farm. The weights are calculated directly from the DEA model, so no arbitrary assumptions on the importance of each burden and output are required. The weights are applied on the *absolute* levels of the burdens (and outputs), i.e. no allocation of burdens to milk or beef production is necessary. They also cancel out the different units of measurement of the different burdens and outputs, making the summations in the numerator and denominator meaningful.

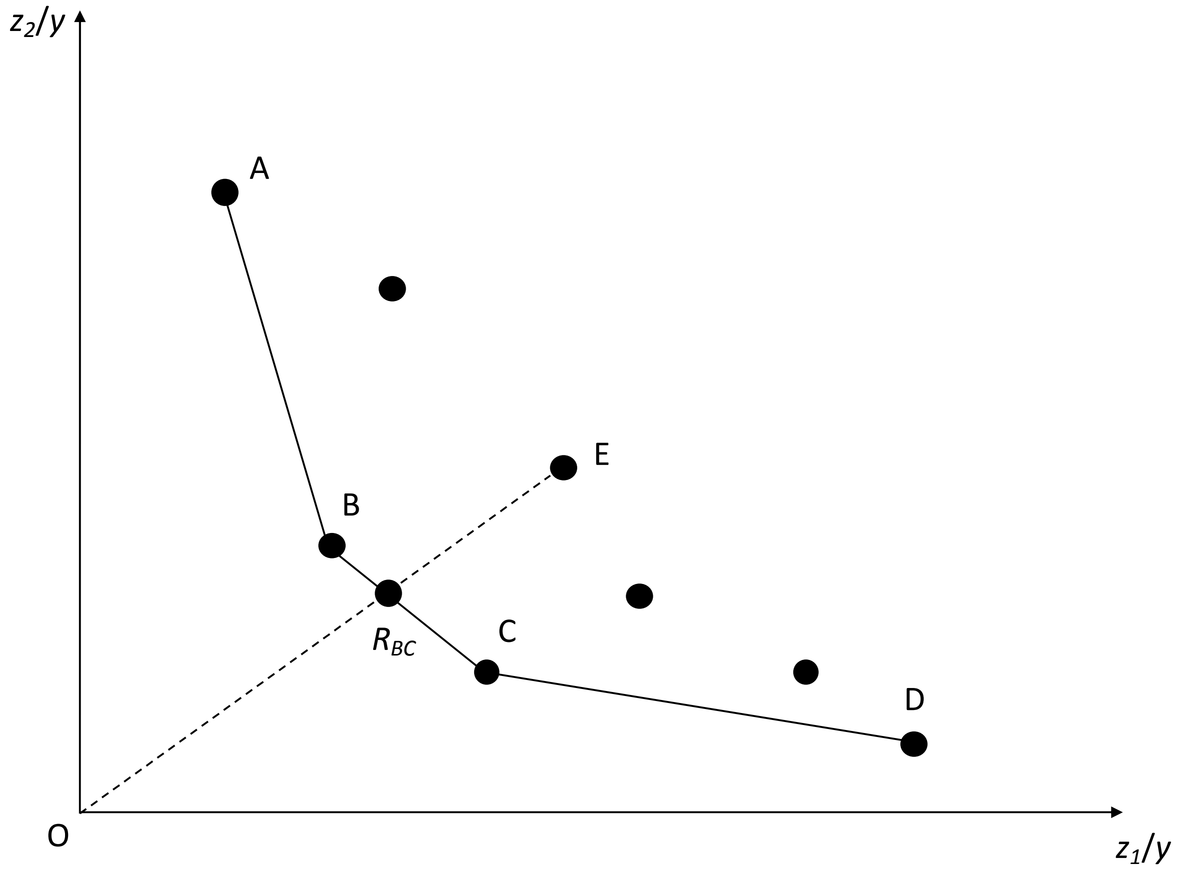

Figure S1. A DEA efficient frontier ABCD in the two-burden – single-output case.

Combining burdens and outputs with DEA is greatly advantageous for creating overall or 'global' indicators of farm environmental footprints. Mathematical descriptions of DEA models, their settings and associated theories are extensively covered in classic DEA textbooks (Bogetoft and Otto 2011, Cooper *et al* 2007) as well as in agricultural studies (Jan *et al* 2012, Picazo-Tadeo *et al* 2011, Soteriades *et al* 2016). Extensively discussing models and theories is beyond the scope of our study. However, we do present below the DEA model we used and justify our choice.

Suppose that there are *n* decision-making units (DMUs, e.g. dairy farms) each producing *m* burdens and *s* outputs, denoted as z_i $(i = 1, \dots, m)$ and y_r $(r = 1, \dots, s)$ respectively. The DEA inefficiency score of the j-th DMU, denoted as DMU_o, is given by the following fractional programming model:

Model 1:

$$\max_{w,u}\theta = \frac{w_1y_{1o} + w_2y_{2o} + \cdots + w_sy_{so}}{v_1z_{1o} + v_2z_{2o} + \cdots + v_mz_{mo}}$$

subject to

$$\frac{w_1y_{1j} + w_2y_{2j} + \cdots + w_sy_{sj}}{v_1z_{1j} + v_2z_{2j} + \cdots + v_mz_{mj}} \leq 1\ (j = 1, \dots, n)$$

$$v_1, v_2, \dots, v_m \geq 0$$

$$w_1, w_2, \dots, w_s \geq 0.$$

The constraints mean that the ratio of 'virtual output' over 'virtual burden' should be at most one for every DMU. The objective is to obtain weights w_r and v_i that maximize the ratio of DMU_o. Because of the constraints, the optimal objective value θ^* is at most one[1]. See Cooper *et al* (2007, p 23).

Model 1 can be easily converted into a simple linear program (Cooper *et al* 2007):

Model 2[2]:

$$\max_{w,u}\theta = w_1y_{1o} + w_2y_{2o} + \cdots + w_sy_{so}$$

subject to

$$v_1z_{1o} + v_2z_{2o} + \cdots + v_mz_{mo} = 1$$

$$w_1y_{1j} + w_2y_{2j} + \cdots + w_sy_{sj} \leq v_1z_{1j} + v_2z_{2j} + \cdots + v_mz_{mj}, (j = 1, \dots, n)$$

$$v_1, v_2, \dots, v_m \geq 0$$

$$w_1, w_2, \dots, w_s \geq 0.$$

In practice, the dual of Model 2 is often preferred, as it is easier to solve[3]:

[1] Note that, for simplicity, and contrary to the models presented in the main article, we have here omitted the subscript 'o' from the DEA weights and scores, as well as from the lambda, pi and tau variables, and slacks later on (Models 3 & 4).
[2] When linearizing Model 1, the weights $w_1, w_2, \dots, w_s \geq 0$ and $v_1, v_2, \dots, v_m \geq 0$ are in fact multiplied by a positive variable *t* in the objective function and constraints (Cooper *et al* 2007). Thus, strictly speaking, we should have changed the weights' symbols in Model 2 to reflect this change, e.g. $\mu_1 = tw_1$ etc. We avoided doing so for consistency. After all, the weights are variables to be estimated by the model, so they can be represented by any arbitrary choice of letters.
[3] In addition, Model 3 describes the situation illustrated in Figure 1 (Cooper *et al* 2007).

Model 3:

$$\min_{\lambda} \theta$$

subject to

$$\theta z_{io} \geq \lambda_1 z_1 + \lambda_2 z_2 + \cdots + \lambda_n z_n \ (i = 1, \dots, m)$$

$$y_{ro} \leq \lambda_1 y_1 + \lambda_2 y_2 + \cdots + \lambda_n y_n \ (r = 1, \dots, s)$$

$$\lambda_j \geq 0 \ (j = 1, \dots, n).$$

The constraints of Model 3 tell us that DMU_o is benchmarked against a virtual DMU whose burdens and outputs are a linear combination of the burdens and outputs, respectively, of all DMUs (e.g. DMU E in Figure S1 is benchmarked against R_{BC} that is a linear combination of B and C). These linear combinations are obtained from the non-zero lambda values and indicate by how much DMU_o should proportionally reduce its burdens to produce the same output as its virtual benchmark. When $\lambda_k = 1$ and k corresponds to DMU_o, then the benchmark of DMU_o is itself, which means that it is 100% efficient. When $\lambda_k = 1$ and k does not correspond to DMU_o, then the benchmark of DMU_o is another real DMU, rather than a virtual (i.e. linear combination) of DMUs.

Model 3 is the input-oriented ('burden-oriented' in our case) radial DEA model that maximizes a farm's efficiency by proportionally (i.e. radially) reducing inputs (burdens in our case) for the given outputs (Figure S1; Cooper *et al* 2007). Model 3 assumes a constant returns-to-scale specification (CRS), i.e. it assumes that doubling the inputs will double the outputs (Bogetoft and Otto 2011). Although this is an important assumption that may not reflect what is observed in practice, the CRS specification measures the overall efficiency of a DMU regardless of whether its inefficiencies are attributed to scale or management. This was desirable in our study, as our interest lied in capturing all sources of exhibited inefficiencies, and in creating a ratio of virtual burdens over virtual outputs analogous to partial ratios of burdens over outputs. For further discussion on the choice of returns-to-scale in the context of agriculture see footnote 1 in Picazo-Tadeo *et al* (2011).

Slacks

As mentioned in the main text, one can calculate burden and output slacks for Model 3. The formulas for obtaining the slacks is presented below, following the modified version of Model 3 to accommodate assurance region constraints.

When adding the assurance region constraints presented in the main article, Model 3 slightly changes. In this case, two new variables are introduced in the dual, namely $\boldsymbol{\pi}$ and $\boldsymbol{\tau}$, that correspond to the assurance regions for the inputs and outputs respectively. Variables $\boldsymbol{\pi}$ and $\boldsymbol{\tau}$ are vectors (hence the bold font) with dimensions $(2m-2)\times 1$ and $(2s-2)\times 1$ respectively. Model 3 then becomes (Cooper et al 2007):

Model 4:

$$\min_{\boldsymbol{\lambda},\boldsymbol{\pi},\boldsymbol{\tau}} \theta$$

subject to

$$\theta \boldsymbol{z}_o - X\boldsymbol{\lambda} + P\boldsymbol{\pi} \leq \boldsymbol{0}$$

$$Y\boldsymbol{\lambda} + Q\boldsymbol{\tau} \geq \boldsymbol{y}_o$$

$$\boldsymbol{\lambda}, \boldsymbol{\pi}, \boldsymbol{\tau} \geq \boldsymbol{0},$$

where

$$P = \begin{pmatrix} l_{12} & -u_{12} & l_{13} & -u_{13} & \ldots & \ldots & \ldots & \ldots \\ -1 & 1 & 0 & 0 & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & -1 & -1 & \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \end{pmatrix}$$

and

$$Q = \begin{pmatrix} L_{12} & -U_{12} & L_{13} & -U_{13} & \ldots & \ldots & \ldots & \ldots \\ -1 & 1 & 0 & 0 & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & -1 & -1 & \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \end{pmatrix}.$$

Note that the bold font in Model 4 refers to vectors. We chose this alternative, 'vectorized' way of presenting this model for better presentation purposes, given the size and complexity of tables P and Q.

Now, given the optimal values for θ, $\boldsymbol{\lambda}$, $\boldsymbol{\pi}$ and $\boldsymbol{\tau}$, the burden and output slacks can be calculated with the following formulas (Cooper et al 2007):

$$\boldsymbol{s}^{-*} = \theta^* \boldsymbol{x}_o - X\boldsymbol{\lambda}^* + P\boldsymbol{\pi}^*$$

and

$$\boldsymbol{s}^{+*} = -\boldsymbol{y}_o + Y\boldsymbol{\lambda}^* + Q\boldsymbol{\tau}^*,$$

where the asterisk denotes optimal values.

Supplementary results

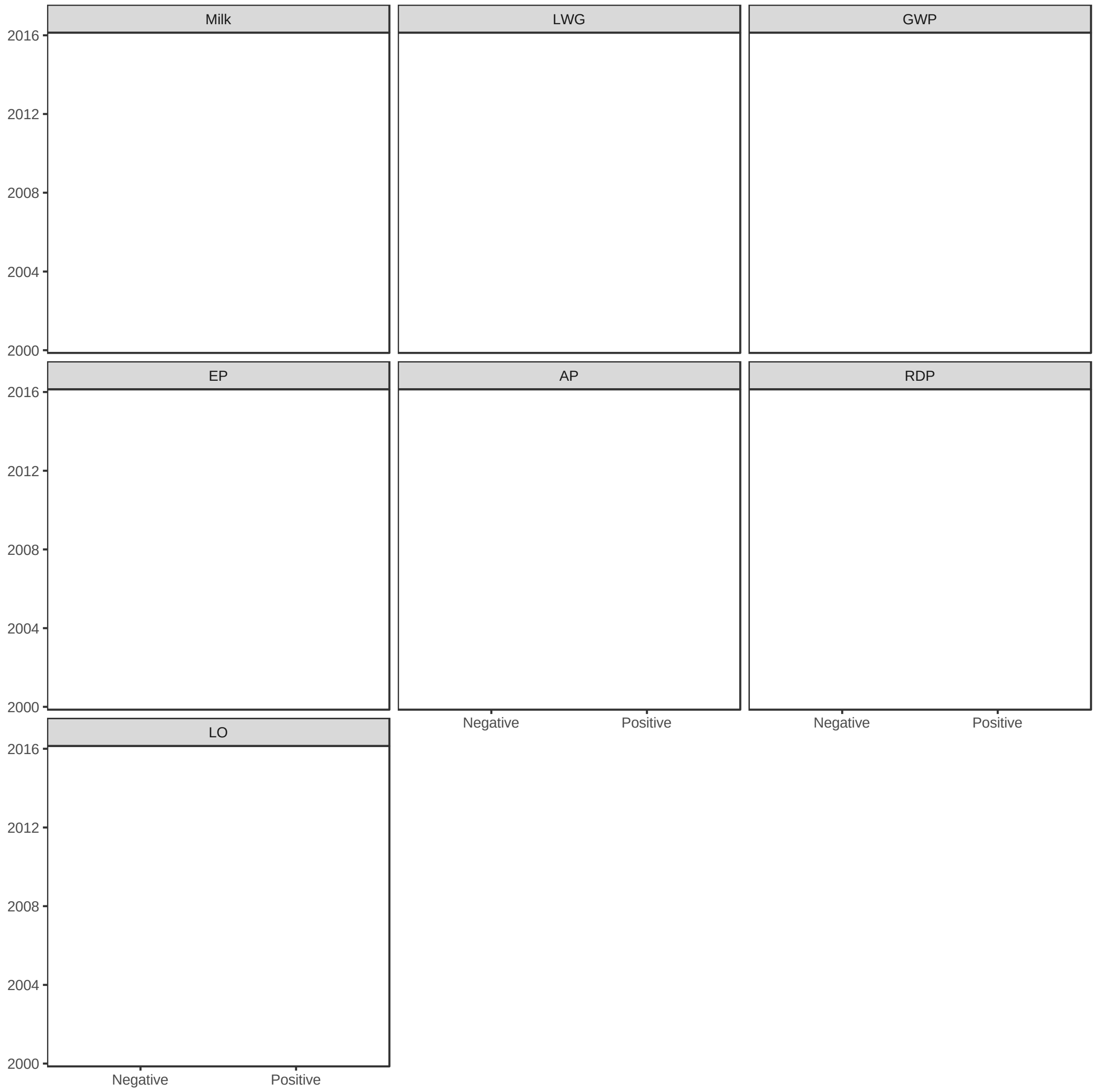

Figure S2. Signs of output slacks (i.e. shortfalls relative to benchmark(s)) and burden slacks (i.e. excesses relative to benchmark(s)) of inefficient farms from model *DEA-milk focussed* for all nine permutations. For better presentation, a 10% sample was drawn from each permutation.

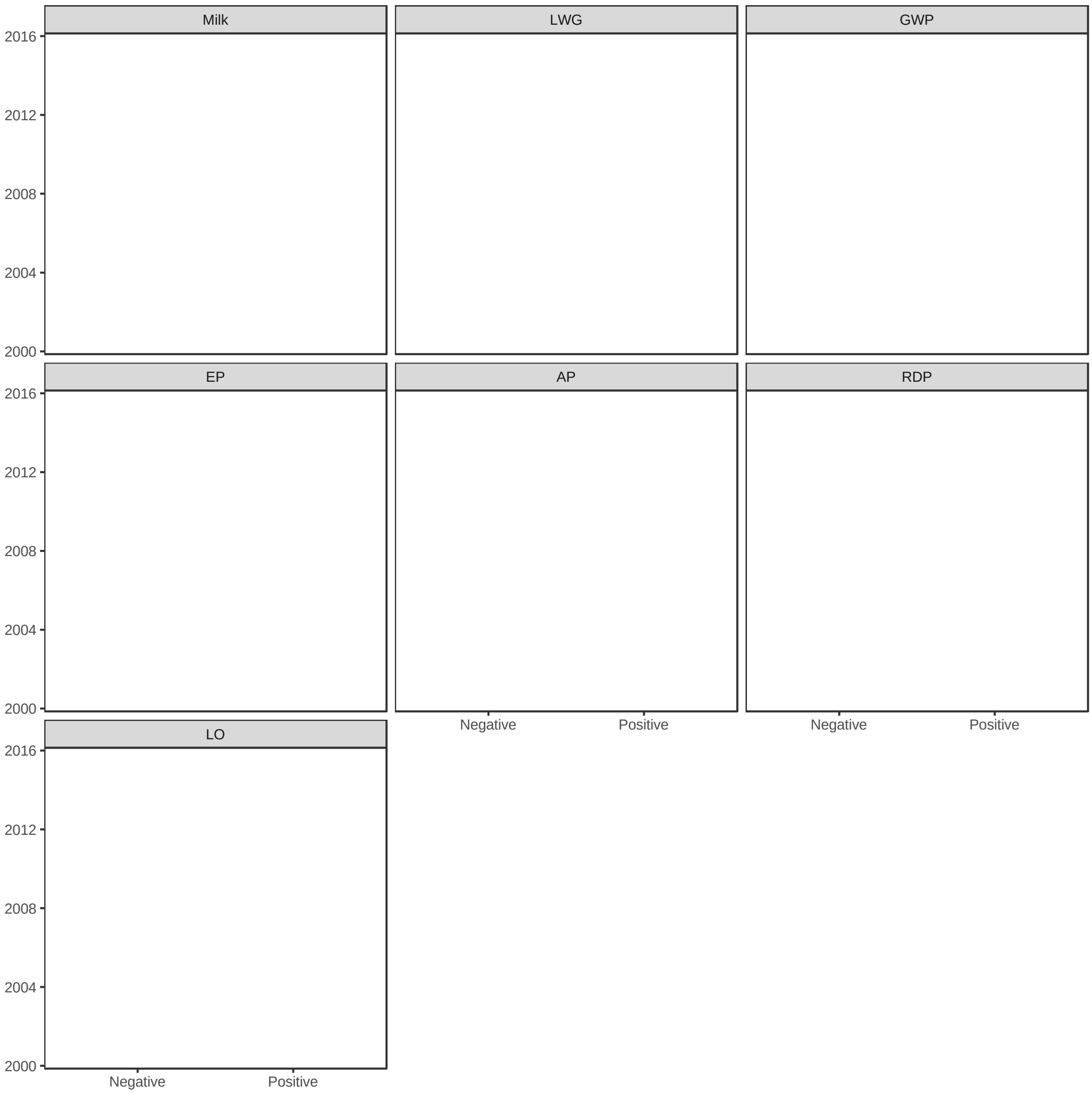

Figure S3. Signs of output slacks (i.e. shortfalls relative to benchmark(s)) and burden slacks (i.e. excesses relative to benchmark(s)) of inefficient farms from model *DEA-milk & beef* for all 36 permutations. For better presentation, a 2.5% sample was drawn from each permutation.

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***Declaration of Interest Statement**

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

***Credit Author Statement**

Conceptualization	ADS, AF, DS, JMG
Methodology	ADS
Software	ADS
Validation	AF, DS, JMG
Formal analysis	ADS
Data Curation	ADS, JMG
Writing - Original Draft	ADS
Writing - Review & Editing	ADS, AF, DS, JMG
Visualization	ADS
Supervision	JMG
Project administration	JMG
Funding acquisition	JMG